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METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR THE CLASSIFICATION OF A SEQUENCE OF INPUT QUANTITIES UPON EMPLOYMENT OF A NEURAL NETWORK, NEURAL NETWORK AND ARRANGEMENT FOR THE TRAINING OF A NEURAL NETWORK

5   The invention is directed to a method for training a neural network, to a method for the classification of a sequence of input quantities upon employment of a neural network as well as to a neural network and an arrangement for training a neural network.

A neural network comprises neurons that are at least partially connected to 10 one another. Input neurons of the neural network are supplied with input signals as input quantities supplied to the input neurons. The neural network usually comprises a plurality of layers. A respective neuron generates a signal dependent on input quantities supplied to a neuron of the neural network and on an activation function provided for the neuron, said signal being in turn supplied to neurons of a further 15 layer as input quantity according to a prescribable weighting. An output quantity dependent on quantities that are supplied to the output neuron of neurons of the preceding layer is generated in an output neuron in an output layer. There are currently essentially two approaches in view of the questions as to the form in which information is stored in a neural network.

20   A first approach assumes that the information in a neural network is encoded in the spectral domain. Given this approach, a chronological sequence of input quantities is encoded such that a respective input neuron is provided for each time row value of a chronological sequence of the input quantities, the respective time row value being applied to this input neuron.

25   Given a neural network that is designed according to this approach, a hyperbolic tangent (tanh) is usually employed as activation function.

This first type of neural network is referred to below as static neural network.

What is particularly disadvantageous about this approach is that it is not possible with a static neural network to explicitly consider a dynamics of a process subject to a technical system in the internal coding of the sequence of input quantities.

The Time Delay Neural Networks (TDNN) known from [4] attempt to counter this disadvantage in that, given a plurality of sequences of input quantities, a respective input neuron is provided for each sequence and for each time row value. This approach particularly exhibits the disadvantage that the dimension of the input space -- represented by the plurality of input neurons -- increases exponentially with an increasing plurality of different sequences of input quantities to be taken into

10   consideration.

An increasing plurality of neurons in the neural network, moreover, involves an increased training outlay upon employment of a plurality of training data that increases with an increasing plurality of neurons. A training of a static neural network becomes highly calculation-intensive under these conditions or, respectively,

15   can practically no longer be implemented.

A gradient-based training method, for example the back-propagation method, is usually utilized for training a static neural network.

[3] also discloses a training method for a static neural network that is referred to as the ALOPEX method. In this method, the training of a static neural

20   network is viewed as an optimization problem. In this case, the goal of the optimization is a minimization of a error criterion E taking weightings that are present in the static neural network and with which the connections between neurons are weighted into consideration for a predetermined training data set with training data.

A training datum is a tuple that [...] input quantities, for example state

25   quantities of a technical system or, respectively, boundary conditions that a technical system is subject to and that are supplied to a technical system as well as an output quantity determined under the boundary conditions and that the technical system forms for the input quantities.

The ALOPEX method shall be explained in greater detail later in

30   conjunction with the exemplary embodiment.

A second approach can be seen therein that the information about a system is encoded in the time domain and in the spectral domain. An artificial neural network that does justice to this approach comprises what are referred to as pulsed neurons and is known from [2].

According to [1], a pulsed neuron is modelled such that the behavior of a pulsed neuron with respect to an external stimulation, which is referred to below as input quantity, is described by a stochastic differential equation of the Itô type according to the following rule:

$$dV(t) = \left(-\frac{V(t)}{\tau} + \mu\right)dt + \sigma dW(t) + w dS(t).$$ (1)

In the rule (1), dW(t) references a standard Wiener process. A predetermined constant τ describes a delay of a membrane potential V(t) of the modelled neuron without input quantity that is adjacent at the neuron. The model simulates the behavior of a biological neuron. For this reason, a pulsed neuron is also referred to as biologically oriented neuron.

Further, S(t) references a coupling of the neuron with another neuron, i.e. the following applies:

$$s(t) = \frac{d}{dt} S(t) = \sum_i \delta(t - t_i),$$ (2)

whereby t_i references an arrival time at which an external impulse arrives at an input of a neuron. A soma-synaptic intensity is modelled by a synaptic quantity w.

In this model, the pulsed neuron generates a pulse when the membrane potential V(t) reaches a predetermined threshold Θ. After the pulse is generated, the membrane potential V(t) of the neuron is reset to a predetermined initialization potential value V(0).

A time sequence of pulses is thus described according to the following rule:

$$t_0', \ldots, t_k', \ldots,$$ (3)

and satisfies the following rule:

$$o(t) = \sum_k \delta\left(t - t_k'\right).$$

(4)

It is also known from [1] that, given the assumption of the above-described model for a pulsed neuron, a discrimination value I(T) can be formed that indicates the dependability with which a sequence of input quantities is correctly classified in view of the training data employed for a training of the neural network.

The discrimination value I(T) is dependent on pulses that are formed by the pulsed neurons within a time span [0; T] as well as on a training sequence of input quantities that are supplied to the neural network. The discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \left\{ \begin{matrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{matrix} \right\} \right),$$

(5)

whereby

- s references the input quantities,

- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],

- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],

- N references a plurality of pulsed neurons contained in the neural network.

A stochastic differential equation of the Itô type derives for a neural network with a plurality of N neurons described according to the following rule:

$$dV_i(t) = \left(-\frac{V_i(t)}{\tau} + \mu\right)dt + \sigma dW_i(t) +$$

$$+ \sum_{j=1}^{N} w_{ij} \sum_k \delta\left(t - t_{k-\Delta_{ij}}^{(j)}\right)dt + I_i(t)dt$$

(6)

whereby

- V_i (t) references a membrane potential of the ith neuron (i = 1, ..., N),

- N references a plurality of neurons contained in the neural network,

- w_{ij} respectively references a weighting of a coupling between the ith and the jth neuron, clearly a synaptic intensity between the neurons i and j,

- Δ_{ij} references a prescribable axional delay of a signal between the neurons i and j,

- I_i(t) references an external stimulation signal of the neuron i.

[4] discloses a training method for a neural network. Given this method, the neural network is linked such in a control circuit with the model of a technical system that the neural network outputs at least one manipulated variable to the model as output quantity, and the model generates at least one regulating variable from the manipulated quantity supplied by the neural network, said at least one regulating variable being supplied to the neural network as input quantity. The regulating variable is superimposed with a noise having a known noise distribution before it is supplied to the model. As a reaction to the regulating variable modified by the impressed noise, the weightings of the neural network are set as follows: A cost function evaluates whether the change in weighting at the network has effected an improvement of the regulating variable with respect to a rated behavior of the model, and such weightings are favored by the cost function.

The invention is based on the problem of specifying a method as well as an arrangement for training a neural network having pulsed neurons. The invention is also based on the problem of specifying a method for the classification of a sequence of input quantities upon employment of a neural network having pulsed neurons as well as specifying a neural network having pulsed neurons.

The problems are solved by the methods and the arrangement as well as by the neural network having the features of the independent patent claims.

A method for training a neural network that contains pulsed neurons comprises the following steps:

a)   the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b)   the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c)   the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

A method for the classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained according to the following steps comprises the following steps:

a)   the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b)   the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c)   the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time

span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

-- the sequence of input quantities is supplied to the neural network;

d)   a classification signal is formed that indicates what kind of sequence of input quantities the supplied sequence is.

A neural network that contains pulsed neurons has been trained according to the following steps:

a)   the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b)   the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c)   the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

An arrangement for training a neural network that contains pulsed neurons comprises a processor that is configured such that the following steps can be implemented:

a)   the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b)   the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c)   the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

The invention makes it possible to classify a time sequence of input quantities with a neural network what contains pulsed neurons, whereby it is assured that, given optimized classification dependability, a minimized plurality of time values must be supplied to the neural network for classification.

Preferred developments of the invention derive from the dependent claims.

An optimization method that is not gradient based is preferably employed for the maximization of the first discrimination value and/or the second discrimination value, preferably an optimization method based on the ALOPEX method.

The first discrimination value preferably satisfies the following rule:

$$I(T) = I\left(s; \left\{\begin{array}{l} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{array}\right\}\right), \quad (7)$$

whereby

•   s references the input quantities,

- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],

- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],

- N references a plurality of pulsed neurons contained in the neural network.

In a further development, the first discrimination value satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out)) dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} +$$
$$+ \sum_{j=1}^{s} p_j \int p\left(out\Big|s^{(j)}\right) \cdot \ln\left(p\left(out\Big|s^{(j)}\right)\right) dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} \qquad (8)$$

with

$$p(out) = \sum_{j=1}^{s} p_j p\left(out\Big|s^{(j)}\right), \qquad (9)$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,

- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,

- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

The training sequences of input quantities are preferably measured physical signals.

The methods and the arrangements can thus be utilized in the framework of the description of a technical system, particularly for describing or, respectively, investigating a multi-channel signal that has been registered by an electroencephalograph and describes an electroencephalogram.

The methods and the arrangements can also be utilized for the analysis of multi-variant financial data in a financial market for the analysis of economic relationships.

The described method steps can be realized both in software for the

5   processor as well as in hardware, i.e. with a specific circuit.

An exemplary embodiment of the invention is shown in the Figures and is explained in greater detail below.

Shown are:

Figure 1   a flowchart wherein the individual method steps of the exemplary

10   embodiment are presented;

Figure 2   a sketch of an electroencephalograph and a patient for whom a electroencephalogram is produced;

Figure 3   a sketch of a neural network according to the exemplary embodiment;

Figure 4   a sketch on the basis whereof the principle underlying the exemplary

15   embodiment is shown.

Figure 2 shows a patient 200 to whose head 201 sensors 202, 203, 204, 205 and 206 are attached for the registration of brain stomata [sic; should probably read "currents"]. Electrical signals 207, 208, 209, 210 and 211 picked up by the sensors 202, 203, 204, 205, 206 are supplied to an electroencephalograph 220 via a

20   first input/output interface 221. The electroencephalograph 220 comprises a plurality of input channels. Via the input/output interface 221, which is connected to an analog-to-digital converter 222, the electrical signals are supplied to the electroencephalograph 220 and digitalized in the analog-to-digital converter 222, and each registered electrical signal is stored in a memory 223 as a sequence or time row

25   values.

A sequence of time row values is thus characterized by a sampling interval as well as by a time duration, referred to below as time span, during which a respective electrical signal is registered. The memory 223 is connected to the analog-to-digital converter 222 as well as to a processor 224 and a second input-output

30   interface 225 via a bus 226.

A picture screen 228 (via a first cable 227), a keyboard 230 (via a second cable 229) and a computer mouse 232 (via a third cable) are also connected to the second input/output interface 225.

Results of the examination of the patient 200 are shown on the picture

5   screen 228. A user (not shown) can make inputs into the system via the keyboard 230 or, respectively, the computer moose 232.

The processor 224 is configured such that the method steps described later can be implemented.

A respective sequence of time row values as well as a particular about the

10   class of time row values to which the sequence of time row values is to be allocated form a training datum.

A plurality of training data form a training data set with which a neural network 301 described later is trained.

Figure 3 shows the neural network 301 with pulsed neurons.

15   A sequence 306, 307, 308 of time row values is respectively applied to a respective input neuron 302, 303, 304 of an input layer 305. A particular as to whether the sequence 306, 307, 308 of the time row values, broadly referred to as input pattern 306, 307, 308, is a matter of an input pattern 306, 307, 308 of a first class or a matter of an input pattern 306, 307, 308 of a second class is allocated to

20   each applied sequence 306, 307, 308 of time row values in the framework of the training method.

A respective input neuron 302, 303, 304 is respectively connected to an intermediate neuron 309, 310, 311 of an intermediate layer 312 via a weighted connection 313, 314, 315.

25   The intermediate neurons 309, 310, 311 are connected to one another via connections 316, 317, 318, 319, 320, 321 that are likewise weighted.

The intermediate neurons 309, 310, 311 are also connected to further pulsed neurons 322, 323, 324 via weighted connections 325, 326, 327, 328, 329 and 330.

30   The pulsed neurons respectively comprise the above-described behavior that is presented in [2].

The intermediate neurons 309, 310, 311 are connected to a plurality of intermediate neurons 309, 310, 311; the respective, further pulsed neurons 322, 323, 324 are respectively connected to exactly one intermediate neuron 309, 310, 311. In this way, it is possible to model a far-reaching influencing between neurons of a neural network as well as a local influencing of neurons within the neural network.

An output neuron 331 is connected to the further pulsed neurons 322, 323, 324 via weighted connections 332, 333 and 334. The output neuron 331 forms an output signal 335 that indicates the class to which the input pattern 306, 307, 308 belongs.

In the training phase of the neural network 301, the output quantity 335 is compared to the classification particular allocated to the respective input pattern, and an error signal E is formed that is employed for adapting the weightings of the connections between the neurons present in the neural network 301.

The method according to the ALOPEX method, which is not gradient based, is utilized as the training method in the framework of this exemplary embodiment. The goal of the ALOPEX method is the minimization of an error criterion E taking into consideration and adapting the weightings w_{bc} for a training dataset.

The ALOPEX is explained in greater detail below.

A neuron b is connected to a neuron c via a connection that is weighted with the weighting w_{bc}. During an fth iteration, the weighting w_{bc} is updated according to the following rule:

$$w_{bc}(f) = w_{bc}(f - 1) + \delta_{bc}(f), \qquad (10)$$

whereby δ_{bc} (f) references a small positive or negative, predetermined step width δ according to the following rule:

$$\delta_{bc}(f) = \begin{cases} -\delta & \text{with a probability} \\ +\delta & \text{with a probability} \end{cases} \qquad \frac{p_{bc}(f)}{1 - p_{bc}(f)} . \qquad (11)$$

A probability $p_{bc}(f)$ is formed according to the following rule:

$$p_{bc}(f) = \frac{1}{1 + e^{-\frac{C_{bc}(f)}{T(f)}}} ,$$

(12)

whereby $C_{bc}(f)$ is formed according to the following rule:

$$C_{bc}(f) = \Delta w_{bc}(f) \cdot \Delta E(f) .$$

(13)

$T(f)$ references a prescribable value. $\Delta w_{bc}(f)$ and $\Delta E(f)$ reference the weighting changes $\Delta w_{bc}(f)$ of the weightings w_{bc} or, respectively, the change $\Delta E(f)$ of the error criterion during the preceding two iterations according to the rules:

$$\Delta w_{bc}(f) = w_{bc}(f - 1) + w_{bc}(f - 2),$$

(14)

$$\Delta E_{bc}(f) = E_{bc}(f - 1) + E_{bc}(f - 2) .$$

(15)

The predetermined value $T(f)$ is updated every F iterations according to the following rule:

$$T(f) = \frac{1}{FM} \sum_{b} \sum_{c} \sum_{f'=f-F}^{f-1} |C_{bc}(f')|$$

(16)

when f is a whole multiple of F, and

$$T(f) = T(f - 1) \quad \text{otherwise,}$$

(17)

whereby M references a plurality of connections in the neural network 301.

Equation (16) can be simplified to form the following rule:

$$T(f) = \frac{\delta}{F} \sum_{f'=f-F}^{f-1} |\Delta E(f')| .$$

(18)

The neural network 301 is trained according to the above-described training method upon employment of the training dataset.

Further, a first discrimination value I(T) for the neural network 301 is formed according to the following rule:

$$I(T) = I\left(s; \begin{bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{bmatrix}\right), \quad (19)$$

whereby

- s references the input quantities,

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- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],

- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],

- N references a plurality of pulsed neurons contained in the neural network.

10   The first discrimination value I(T) clearly corresponds to the difference of the following entropies:

$$I(T) = H(out) - \langle H(out|s) \rangle_s, \quad (20)$$

with

$$H(out) = -\int p(out) \cdot \ln(p(out)) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} \quad (21)$$

and

$$\langle H(out|s) \rangle_s = -\sum_{j=1}^{s} p_j \int p\left(out|s^{(j)}\right) \cdot \ln\left(p\left(out|s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)}. \quad (22)$$

The first discrimination value I(T) thus derives according to the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out)) dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} +$$

$$+ \sum_{j=1}^{s} p_j \int p\left(out\middle|s^{(j)}\right) \cdot \ln\left(p\left(out\middle|s^{(j)}\right)\right) dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} \quad (23)$$

with

$$p(out) = \sum_{j=1}^{s} p_j p\left(out\middle|s^{(j)}\right), \quad (24)$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,

- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,

- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

When a maximum first discrimination value I(T) has been determined in the framework of training the neural network 301, then this means that the input pattern 306, 307, 308 observed in the first time span contains enough information in order to classify the input pattern with adequate dependability.

The first discrimination value I(T) is clearly formed (step 101) in the framework of the training for a first time span [0; T] (see **Figure 1**).

In a further step (step 102), a second time span is formed by shortening the first time span: [0; T'], whereby T' < T applies.

For the second time span [0; T'], a second discrimination value I(T') is formed in a further step (step 103) in the same way as described above for the first discrimination value I(T).

The first discrimination value I(T) is compared to the second discrimination value I(T') (step 104).

When the second discrimination value I(T') is the same as the first discrimination value I(T), then a new second time span is formed (step 105) by shortening the second time span [0; T'], and the new second time span is considered to be the second time span (step 106). A second discrimination value I(T') is in turn

5 formed (step 103) for the second time span of the new iteration.

Clearly, this iterative method means that the time span wherein pulses generated by the pulsed neurons are taken into consideration for forming the output signal is shortened until the second discrimination value I(T') is unequal to the first discrimination value I(T).

10 When the second discrimination value I(T') is smaller than the first discrimination value, then the neural network 301 is viewed as being an optimized neural network that was trained in the last preceding iteration wherein the second discrimination value I(T') was not smaller than the first discrimination value I(T) (step 107).

15 The time span respectively taken into consideration is divided into discrete time sub-spans for which the only thing respectively determined is whether a neuron generated a pulse during the time sub-span or not.

In this way, the calculating outlay needed for the training is considerably reduced.

20 For further illustration, the principle is explained again on the basis of **Figure 4**.

Figure 4 shows two continuous processes p1 and p2 that are formed by a set of continuous input signals S1 and S2. Two sequences of input quantities, the input patterns, are present after a corresponding, above-described digitalization. The

25 input patterns are supplied to the trained neural network 401 in an application phase, and a space-time encoding of the processes p1, p2 is clearly implemented on the basis of the time rows for the trained neural network 401.

On the basis of an output signal 402, the trained neural network 401 indicates the kind of process the input pattern involves. The trained neural network

30 401 exhibits the property that, first, the dependability of the optimization is optimized

and, second, a minimum plurality of time row values, i.e. a minimum second time span 403, is required in order to dependably implement the classification.

A few alternatives to the above-described exemplary embodiment are present below:

5   The plurality of inputs, of pulsed neurons as well as output signals is generally arbitrary. The plurality of different sequences of time row values is also arbitrary in the framework of the classification and in the framework of the training. An electroencephalogram analysis is thus possible for an arbitrary plurality of channels for characterizing tumors.

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